

Research Paper

Vegetation phenology on the Qinghai-Tibetan Plateau and its response to climate change (1982–2013)

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ABSTRACT

Using NDVI3g vegetation index, we defined 18 phenology metrics to investigate phenological change on the Tibetan Plateau (TP). Considering the heterogeneity of vegetation phenology, we divided TP into 8 vegetation clusters according to a 1:1000000 vegetation cluster map. For regions where phenology is highly sensitive to climate, we investigated the impact of climate variables, such as temperature, precipitation, and solar radiation on phenology using the partial least squares regression (PLS) method. Results indicated (1) that turning points of the starting date of the growing season (SOS) metrics were in 1997–2000, before which SOS metrics advanced 2–3d/10a. The ending date of the growing season (EOS) and the length of growing season metrics (LOS) turning points were 2005 and 2004–2007, respectively. Before the turning points, the EOS metrics had a delayed tendency of 1–2d/10a, and the LOS metrics also had a prolonging tendency of 1–2d/10a. After the turning points, the significant levels of SOS and EOS metrics' tendency only reached 0.1, and LOS's tendency was insignificant at the 0.1 level. (2) Alpine meadows and alpine shrub meadows changed most intensely on TP. Advanced SOS and delayed EOS were the main reasons of the alpine meadow LOS extension. Advance SOS mainly contributed to the alpine shrub meadow LOS extension. (3) We used meteorological variables, such as temperature, precipitation and solar radiation, to analyze the drastic change of the phenology of alpine meadows and alpine shrub meadows through the PLS method. Temperature was found to be the dominant meteorological variable impacting phenology. In those regions, the previous year autumn and early winter temperature had a positive effect on the SOS phenology. The high temperature in this period would postpone previous year EOS, indirectly delaying SOS in the current year. On the other hand, warming autumn and early winter may slow the fulfilment of chilling requirements and lead to later SOS, which would have a delayed effect on SOS. Except summer, the minimum temperature had a similar effect on vegetation phenology, as average and maximum temperature. Furthermore, the effect of precipitation on phenology fluctuated widely across different months. The previous year autumn and winter precipitation had a negative effect on the SOS phenology, and early spring precipitation had a positive effect. The main factor limiting vegetation development in August was precipitation, and during this month precipitation had a positive impact on the EOS phenology. The influence of solar radiation was mainly during summer and early fall. This study will contribute toward vegetation phenology model improvement.

1. Introduction

Phenology, studying the timing of recurring biological cycles and their relation to climate change, provides an independent measure of how ecosystems are responding to climate change (Linderholm, 2006; Parmesan, 2006; White et al., 2009). It is now acknowledged that

climate change remarkably impacts terrestrial ecosystems (Walther et al., 2002; Kelly and Goulson, 2008; Reichstein et al., 2013; Zhou et al., 2014; Wu et al., 2015). Meanwhile, as an important component of the Earth system vegetation modulates regional and global climate change by biogeochemical and biophysical feedbacks (Field et al., 2007; Peñuelas et al., 2009; Tan et al., 2015). Therefore, monitoring

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vegetation phenology is critical for understanding the vegetation response to a changing climate as well as for enumerating the feedback mechanisms that vegetation response may generate for the climate itself (Cleland et al., 2007; Morisette et al., 2009; Peñuelas et al., 2009; Garonna et al., 2016). Hence, decadal trends and interannual variability of vegetation phenology merits analysis, because they can shed light on the modification of carbon (e.g. Jeong et al., 2012), and water and energy exchange (Obriest et al., 2003) between vegetation and atmosphere (White et al., 2009). Hence, monitoring land surface phenology (LSP) is important for elucidating the land-atmosphere-energy exchange (Shen et al., 2016) and its representation in terrestrial biosphere models (Garonna et al., 2016).

The Qinghai-Tibetan Plateau (QTP), also known as the 'Earth's third pole', is the highest and largest plateau of the globe, covering approximately 2.5 million km² at an average elevation of 4000 m (e.g. Chen et al., 2015). The QTP has a unique vegetation composition and climate properties along with low degree of human interference (e.g. Piao et al., 2011). It has unique climate features, such as intense solar radiation, longer sunshine duration, lower air temperature and pressure, less cloud cover, and discernable seasonal and spatial inhomogeneity of precipitation. These features make the QTP the principle regional driver and amplifier of global climate change (Liu and Chen, 2000; Dong et al., 2012; Che et al., 2014). Numerous studies have shown that vegetation in this region is highly sensitive to climate change (Shen et al., 2011; Dong et al., 2012; Zhang et al., 2013a,b; Che et al., 2014). However, observed climate records of the past three decades show a very substantial climate change on the QTP (Liu and Chen, 2000) which has been characterized by significant warming with a temperature rise of about 0.4 °C per decade (Dong et al., 2012; Wang et al., 2012; Shen et al., 2014). This warming rate is believed to be higher than that for the northern and southern hemispheres as well as for the globe as a whole (Trenberth et al., 2007). Besides, previous studies have pointed out that terrestrial ecosystems on the QTP acted as a small carbon sink (e.g. Zhang et al., 2009; Piao et al., 2011). Hence, climate change and its impact on vegetation phenology on the QTP is a matter of global concern.

Numerous studies have addressed the effect of warming climate on vegetation phenology (e.g. Shen et al., 2014), such as increasing vegetation productivity (Wang et al., 2012; Xu et al., 2011), higher ecosystem respiration (Lin et al., 2011; Tan et al., 2010), loss of species diversity (Klein et al., 2004; Wang et al., 2012), advancing spring phenology (Zhang et al., 2013a,b), glacier retreat (Yao et al., 2012), and thawing of permafrost (Wu et al., 2013). Several of these studies have focused on vegetation growing season, and starting and ending dates of spring and autumn vegetation phenology. However, results of these studies are always not in agreement. Dong et al. (2012) suggested that the regional average growing season length had a significant increasing trend with an increasing rate of 3.29 days/decade, and this change was attributed to an earlier start of the growing season (−1.82 days/decade). They also argued that the variation in the growing season indices throughout the TP during the last 50 years was strongly correlated with elevation. However, Yu et al. (2010) indicated that during 1982–2006 for meadow and steppe vegetation on the QTP, spring phenology initially advanced, followed by retreating in the mid-1990s in spite of continued warming. Together with the advancing end of the growing season for steppe vegetation, this led to a shortening of the growing period. Nevertheless, relations between vegetation growing season and altitude were identified by Ding et al. (2012) and Dong et al. (2012). Chen et al. (2015) reported no continuous advancing trends of green-up dates during 1982–2011, and no turning points in the mid to late 1990s. Therefore, chilling requirements were not suggested as an important driver influencing the green-up response to spring warming (Chen et al., 2015).

The above-mentioned discrepancies in research results and/or scientific viewpoints call for further analysis based on updated long term observed vegetation data and full consideration of potential drivers.

The significance of the current study can be justified, because strong environmental gradients can be expected due to the unique geographical conditions of the QTP (Qin et al., 2009; Shen et al., 2014), which result in spatial heterogeneity of water and temperature conditions, causing diverse phenological responses to warming across the plateau (Shen et al., 2011). Besides, discrepancies in relations between vegetation growing season, spring and/or autumn vegetation phenology, are because vegetation growth or green-up activities should be attributed to more than one driver such as precipitation and temperature. For example, numerous studies have found that precipitation and sunshine duration in the plateau were the major factors for vegetation growth (e.g. Mao et al., 2007; Che et al., 2014). It is therefore necessary to further analyze spatiotemporal variations of vegetation phenology and their relation with climatic factors across the QTP.

Focusing on discrepancies in vegetation phenology and related causes in the QTP, this study investigated the entire vegetation phenology changes via definitions of 18 vegetation phenological metrics. Considering the spatial heterogeneity of water and temperature conditions and related different vegetation responses, this study classified the entire QTP into different vegetation regions and then analyzed vegetation phenology changes for each individual vegetation region. The partial least squares regression model (PLS) was used to analyze the lagging effect of vegetation response to climate change with the aim to differentiate time intervals when climate variables have different influences on vegetation phenology. The objectives of this study therefore are to address: (1) changes in the vegetation phenology on the QTP, and (2) the climate variables that have specific impacts on vegetation phenology across different vegetation regions on the QTP. For accomplishing these objectives, this study defined 18 vegetation phenological metrics, based on NDVI3g data, and the entire QTP was categorized into 8 vegetation regions, based on a vegetation map of scale of 1:1000000. Potential impacts of climatic variables, such as maximum/minimum air temperature, average air temperature, precipitation, and solar radiation on vegetation phenology were analyzed using the PLS model. This study can provide a full picture of vegetation phenology during the period of 1982–2013 and related climatic drivers across the QTP.

2. Data

2.1. Normalized difference vegetation index (NDVI)

NDVI is a vegetation indicator that has been widely used for quantifying vegetation biomass (Kong et al., 2017), growing processes, and phenology. The NDVI dataset analyzed for phenological metrics is the 3rd-generation NDVI by Advanced Very High Resolution Radiometer (AVHRR) instrument from the NOAA satellite series 7, 9, 11, 14, 16, and 17, with spatial resolution of 1/12° and biweekly time step, and covered a period of July 1981–December 2013 (<https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0>). This dataset has been corrected by calibration, view geometry, volcanic aerosols, and other effects that have no relation with vegetation change (Pinzon and Tucker, 2014). The NDVI dataset covering the completed year during 1982–2013 was used in this study. Due to the spatial heterogeneity of vegetation phenology, TP was subdivided into 9 clusters based on a 1:1000000 vegetation cluster map (Fig. 1), wherein tropical rainforest was removed because of its less than obvious NDVI seasonal change. Thus, altogether 8 clusters were included.

2.2. Meteorological data

Average temperature (Tavg), maximum temperature (Tmax), minimum temperature (Tmin), precipitation (Precip), and insolation (Radiation) were used to investigate climatic impact on phenology. And the dataset was obtained from the Data Assimilation and Modeling Center for Tibetan Multi-spheres (ftp://hpc.itpcas.ac.cn/Data/DAT-31.0002.02.16.NG_ITPCAS-CCMPD_B_v1.6), institute of Tibetan Plateau

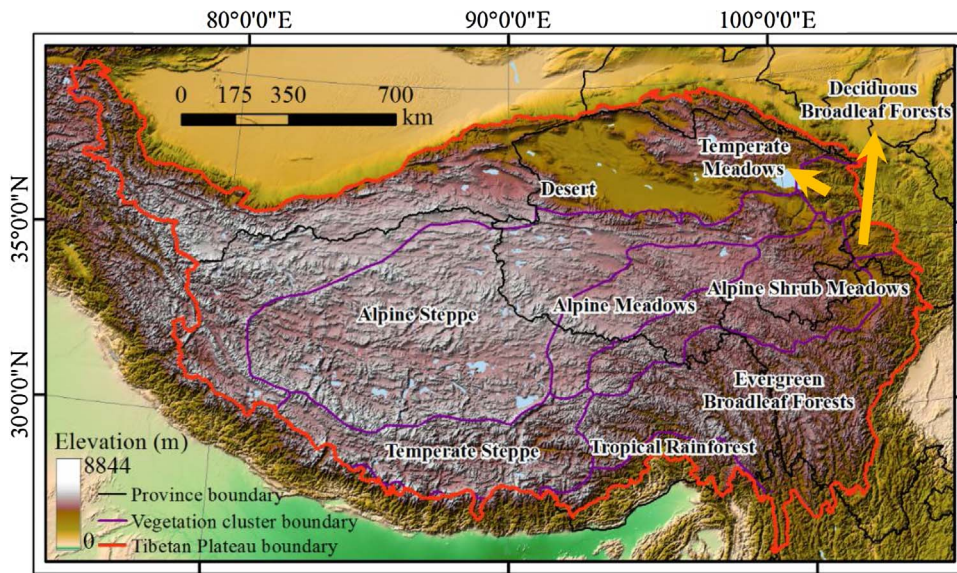


Fig. 1. Spatial distribution of vegetation categories across the Tibetan Plateau, China.

Research, Chinese Academy of Sciences (Chen et al., 2011). The dataset has a spatial resolution of $0.1^\circ \times 0.1^\circ$, two temporal resolution versions, i.e. 3-h and daily, and covered a period of 1979–2016. In PLS regression, meteorological data before previous year of NDVI was needed. Hence, those meteorological data covering the period of 1981–2013 were used in this study. The gridded daily precipitation and insolation data were extracted directly from the daily assimilation product. And the gridded daily Tavg, Tmax and Tmin were derived from 3-h temperature assimilation product.

3. Methods

3.1. Phenological metrics

To avoid systematical error of different phenophases extraction methods, four widely accepted phenophases extraction methods were

used in this study (Fig. 2). In the analysis of phenology variation, abrupt behavior and climatic impact on phenology, only at least two phenological metrics revealed the same phenomenon, then we treated this phenomenon as reliable.

3.1.1. Threshold method (TRS)

In this study, dynamic thresholds defined as $NDVI_{ratio}$ of 20% and 50% were used to determine SOS (start date of the growing season) and EOS (end date of the growing season) (Shen et al., 2014; White et al., 2009):

$$NDVI_{ratio} = \frac{NDVI_t - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (1)$$

where $NDVI_t$ denotes the NDVI value at a given time t ; and $NDVI_{max}$ and $NDVI_{min}$ are, respectively, the maximum and minimum NDVI values in the annual NDVI cycle.

Specifically, the SOS/EOS was defined as the first day of the year

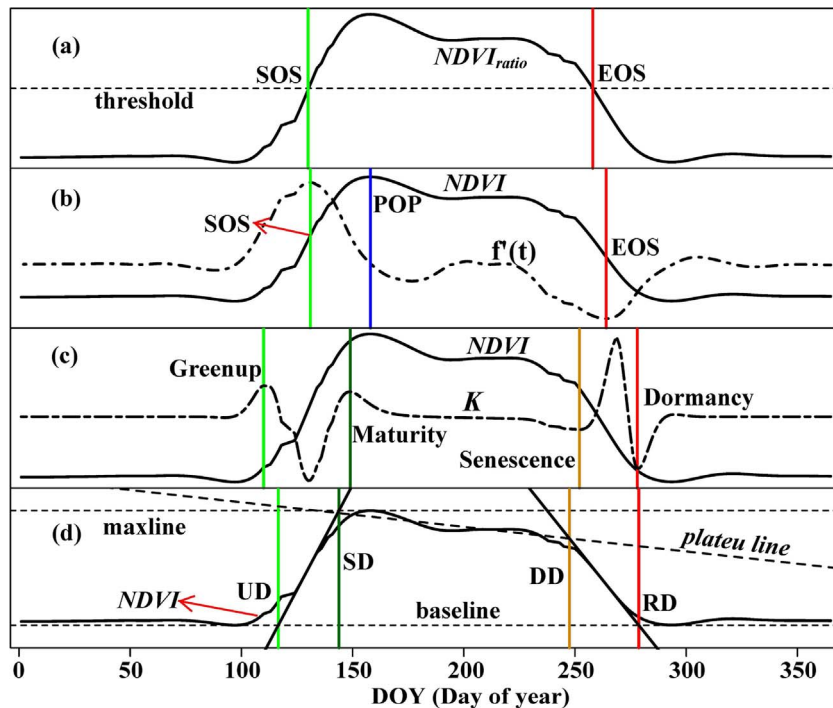


Fig. 2. Methods used to extract phenological metrics in this study. (a): TRS method; (b): Derivative method; (c): Klosterman method; (d): Gu method. UD: update date; SD: stabilization date; DD: downturn date; RD: recession date; POP: peak of season position, and the same denotations in the subsequent sections. SOS: start date of the growing season; EOS: end date of the growing season.

when $NDVI_{ratio}$ value exceeded/was below 0.2 (TRS2) or 0.5 (TRS5). And length of growing season (LOS) was defined as EOS minus SOS. Hence, six phenological metrics were defined by threshold methods, i.e. TRS₂-SOS, TRS₂-EOS, TRS₂-LOS, TRS₅-SOS, TRS₅-EOS and TRS₅-LOS.

3.1.2. Derivative method (DES)

For derivative method, SOS/EOS were defined as the DOY (date of the year) when $f(t)$ was the maximum/minimum; and the DOY of maximum $NDVI$ called pop. So, four phenological metrics were defined by derivative methods, i.e. DES-SOS, DES-EOS, DES-LOS and POP.

3.1.3. Klosterman method

For Klosterman method, four phenological metrics were defined, i.e. Greenup, Maturity, senescence and dormancy. They were defined as the two local maxima (Greenup and Maturity) and two local minima (Senescence and Dormancy) in the change rate of curvature K (Klosterman et al., 2014) and were named after Zhang et al. (2003):

$$K = \frac{f''(t)}{(1 + f'(t)^2)^{1.5}} \quad (2)$$

Where $f''(t)$ and $f'(t)$ are the second- and first-order derivative of the $NDVI$ series.

3.1.4. Gu method

For Gu method (Gu et al., 2009), four phenological metrics were also defined, i.e. update date, stabilization date, downturn date and recession data (abbreviated correspondingly as UD, SD, DD, RD). Maximum and minimum $f(t)$ were used to define slopes of recovery and senescence lines tangent to the curves. The intersection between these lines and baseline and maxline define the four phenophases in the original formulation (Gu et al., 2009). To account for the midseason decrease in $NDVI$, a plateau line was defined as a linear fit to $NDVI$ values between SD and DD (Filippa et al., 2016) in order to adjust the definition of DD.

Generally, spring phenological metrics, also known as SOS metrics, include TRS₂-SOS, TRS₅-SOS, DES-SOS, Greenup, Maturity, UD and SD. Autumn phenological metrics, also known as EOS metrics, include TRS₂-EOS, TRS₅-EOS, DES-EOS, Senescence, Dormancy, DD and RD.

3.2. Piecewise regression

Piecewise regression (Eq. (1)) was used to detect turning points of phenological metrics in this study. Besides, trends before and after phenological metrics' turning points were evaluated using the Mann-Kendall (MK) method (Gocic and Trajkovic, 2013). In order to avoid too few data before or after turning points, α was constrained within the period 1986–2009 (Wang et al., 2011):

$$y = \begin{cases} \beta_0 + \beta_1 t + \varepsilon & t \leq \alpha \\ \beta_0 + \beta_1 t + \beta_2(t - \alpha) + \varepsilon & t > \alpha \end{cases} \quad (3)$$

where t is the time in year; y is the annual phenological metrics; α is the turn point; β_0 , β_1 , β_2 , are regression coefficients, and ε is the residual of the fit.

3.3. Partial least squares regression (PLS)

The PLS has the strength of both principal component analysis and multiple linear regression, which can overcome multicollinearity, especially when explanatory variables are too many. Due to its prominent performance in multiple variables analysis, it has been widely used in phenology research in recent years (Yu et al., 2010; Luedeling and Gassner, 2012; Guo et al., 2015). An algorithm of PLS can be found in Wold et al. (2001), but the procedure for analysis is introduced here. For each phenological metric in every cluster, the multi-annual average metric of MOY (month of Year) was calculated first; and then monthly

meteorological variables, such as Tavg, Tmax, Tmin, precipitation and insolation of July the previous year to August of the current year constituted input as independent variables to PLS, and annual phenological metric as dependent variable. The right number of components for the PLS model was selected based on the root mean squared error of prediction (RMSEP) of PLS model. Usually, RMSEP will decrease with the increasing PLS model components. So, we take the first local minimum rather than the absolute minimum of RMSEP to avoid overfitting. The turning points of RMSEP detected by piecewise method, helped to identify the local minimum RMSEP automatically. After then we inspected RMSEP turning points visually. Finally, those turning points of RMSEP were taken as a suitable number of components of the PLS model. The PLS regression analysis was done using the R software package of 'pls' package (Mevik and Wehrens, 2007).

The Variable Importance in the Projection (VIP) statistic was used to quantify the fractional contribution of each predictor variable to the retained PLS components (Chong and Jun 2005). The VIP values larger than 1 indicate a significant impact of a predictor variable on the variation of response variable (Chong and Jun 2005). Model coefficients of the centered and scaled data against the predictor variables showed the direction and strength of the impact of each variable in the PLS model. Predictor variables with $VIP > 1$ and high absolute values of model coefficients represented the time periods in which the corresponding variables had a strong effect on the timing of the phenological phase (Luedeling and Gassner, 2012).

4. Results

4.1. Average phenology of each individual vegetation cluster

Fig. 3 illustrates the long-term average of 15 phenology metrics of each individual vegetation cluster across the QTP, without consideration of LOS metrics. The growing season of the QTP starts in late April and ends in early October. For spring phenological metrics, Greenup, UD, and TRS₂-SOS are similar, being roughly the late April and early May. Maturity occurs between late July and early September and is subject to evident spatial heterogeneity across the QTP. The peak $NDVI$ concentrates mainly during early August. Besides, the Senescence and DD are concentrated during roughly late September and early September. Middle to late September is the end of the growing season. TRS₂-EOS is subject to larger variability from one vegetation cluster to another and particularly for evergreen broad-leaved forest and temperate steppe regions, which could be because the vegetation coverage of these regions is high and the herbaceous vegetation can retain a certain level of $NDVI$ even after the senescence of dominant vegetation (Fridley, 2012). Therefore, TRS-EOS has a large variability with a smaller threshold value of 0.2. Yu et al. (2010) suggested that a reasonable threshold value for autumn phenology should be 0.6 when the phenology metrics of QTP were quantified when using the TRS method. Meanwhile, TRS₅-EOS is similar to DES-EOS, showing that autumn phenology deduced by TRS5 and DES techniques are close to real-world values. The vegetation approaches senescence after middle and/or late October, and vegetation approaches dormancy after middle November.

4.2. Abrupt behavior of phenology

Spring phenological metrics of the QTP were subject to abrupt change during 1997–2000 (Fig. 4), and this finding was in agreement with the result that 1998 was taken as the turning point of spring phenology (Piao et al., 2011; Shen et al., 2016). Significant turning points were detected for UD, TRS₂-SOS, TRS₅-SOS, and DES-SOS (Fig. 4a, b) and significant decreasing trends of these phenological metrics, i.e. UD, TRS₂-SOS, TRS₅-SOS, and DES-SOS, were detected before turning points with decreasing magnitude of 2.3d/10a, 3.5d/10a, 3.7d/10a, and 3.3d/10a correspondingly. Spring phenology was earlier 2–3d/10a in average before its turning points. However, previous

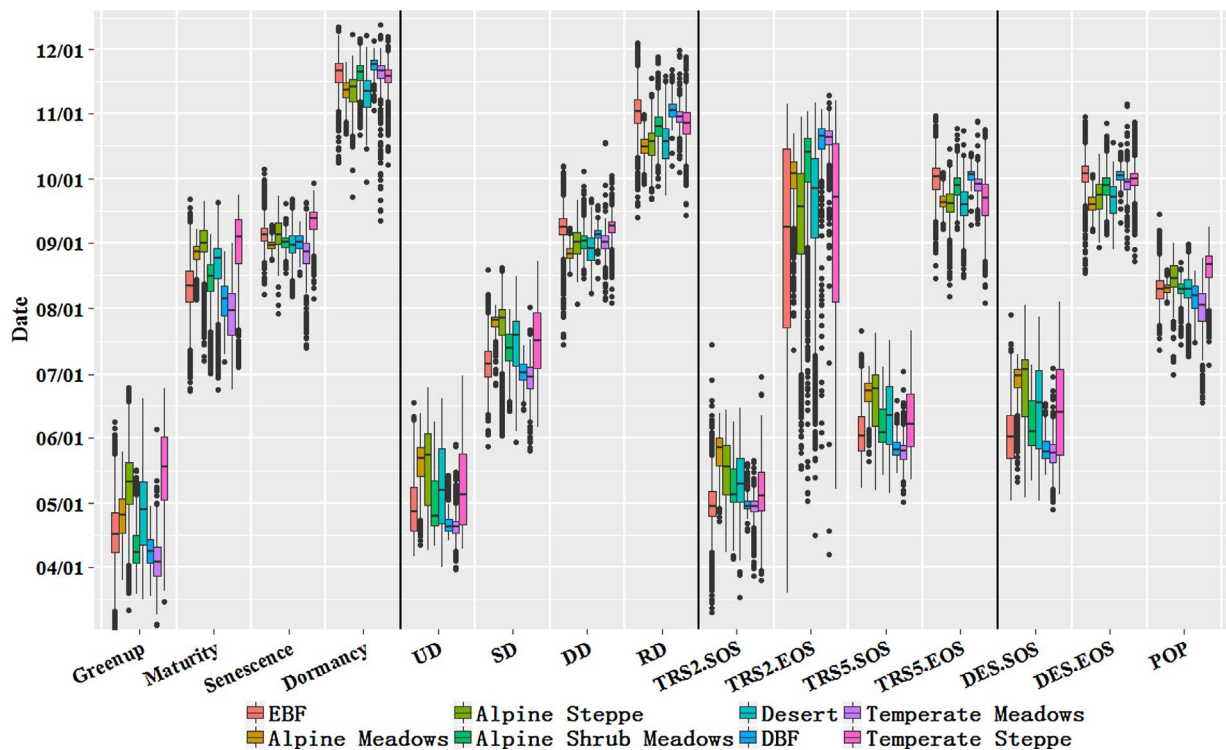


Fig. 3. Long-term average of phenology metrics during 1982–2013 in the Tibetan Plateau for different vegetation clusters. UD: update date; SD: stabilization date; DD: downturn date; RD: recession date; TRS2: 0.2 threshold; TRS5: 0.5 threshold; DES: maximum derivative method; POP: peak of the season position, and the same denotations in the subsequent sections.

studies revealed that spring phenology advanced 4.5–10.2d/10a during 1982–1999 in QTP (Piao et al., 2011; Zhang et al., 2013a,b; Shen et al., 2014). This difference should be attributed to the linear trends detected by this study based on Mann-Kendall trend test method which avoids impacts of outlier data on trend results. After turning points, Update, TRS₅SOS and DES-SOS were delayed with a magnitude of 7–10d/10a. However, after turning points, only the trend of TRS₂SOS was statistically significant. Statistically speaking, after turning points the delayed trend of spring phenology was not supported in this study.

Actually, there was a remarkable discrepancy concerning trends of spring phenological metrics after turning points in the QTP (Yu et al.,

2010; Shen et al., 2011; Zhang et al., 2013a,b). However, it is accepted now that spring phenology in the southwestern QTP is delayed (e.g. Shen et al., 2014), specifically in the temperate grass in southwestern QTP and in the desert in northern QTP. Autumn phenology of QTP was subject to the change point of 2004–2007 (Fig. 5). A significant increasing ending time was identified for Senescence, Dormancy, DES-SOS and TRS₅SOS with an average delay time of 1–2d/10a. Autumn phenology was advanced after the turning points. The delay tendency of Dormancy was –17.6d/10a at the 90% confidence level. The advanced trend of TRS₅SOS was –7.8d/10a at the 95% confidence level. Che et al. (2014) indicated no evident trends of autumn phenology

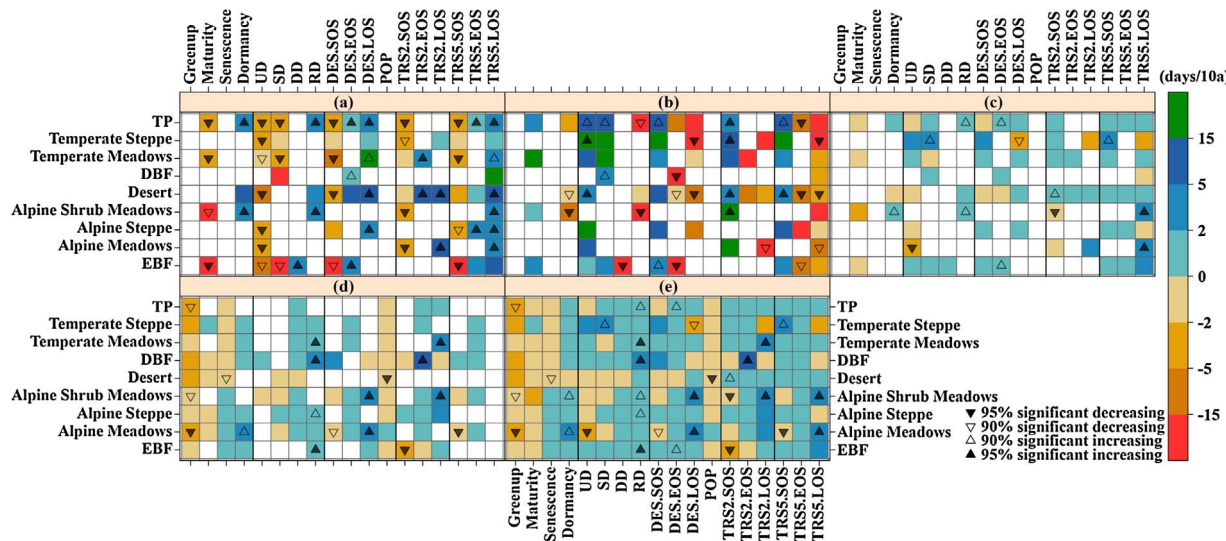


Fig. 4. Trends of phenological metrics before and after turning points and those during the entire period considered in this study. Turning points of phenological metrics were shown in Fig. 6. (a): trends of phenological metrics before the turning point; (b): trends of phenological metrics after the turning point; (c): trends of phenological metrics with significant turning points during the entire studied periods; (d): trends of phenological metrics with not significant turning points during the entire studied periods; and (e): trends of all phenological metrics studied in this study during the entire studied periods.

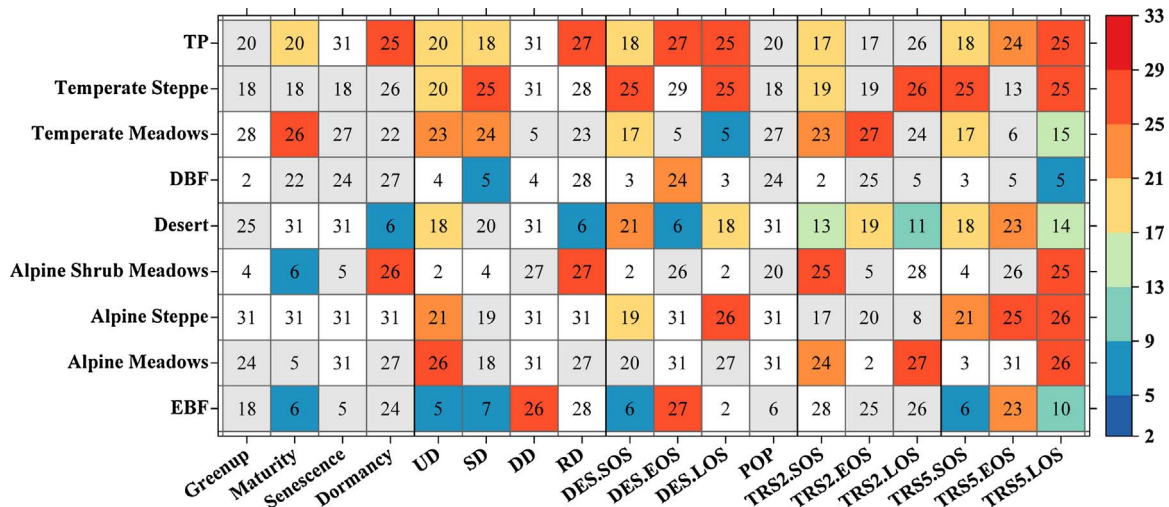


Fig. 5. Turning points of the phenological metrics detected by piecewise regressive method. 2 denotes 1982; 20 denotes 2000, and 30 denotes 2010; White boxes denote that the length of the phenological metrics series before and/or after turning point is less than 5 years; Gray boxes denote that the turning points are insignificant at 90% confidence level.

across the QTP. It can be found from Fig. 5 that the trend of autumn phenology was 0.96d/10a and autumn phenological metrics' trends were insignificant for TRS₅-EOS and Dormancy. Therefore, this study's results do not support the viewpoint about the delay of autumn phenology metrics after turning points. The turning points of LOS metrics and EOS metrics were similar, being around 2005. TRS₅-LOS and DES-LOS lengthened by 2.4d/10a and 1.3d/10a, respectively, before their turning points and the lengthening tendency were insignificant after turning points.

4.3. Climatic impact on phenology

Fig. 6 shows significant increasing trends of maximum temperature across all vegetation clusters. The increase of monthly temperature during November and December reached 0.15 °C/a and a larger increasing magnitude of temperature was observed during winter and

early spring than that across other regions of China. Besides, the seasonal average temperature during winter was subject to the largest increasing magnitude, and relatively smaller increasing magnitude of seasonal average temperature was found during summer and autumn. Furthermore, increasing precipitation was identified across most regions of the QTP and significant increasing precipitation was found mainly during May–August. Meanwhile, solar radiation also had a significant decreasing trend. Because the vegetation of the QTP was dominated by alpine meadow and alpine shrub meadow, this study focused on climatic impacts on the two vegetation types.

4.3.1. Climatic impacts on alpine meadow

It can be seen from Fig. 7a–e that temperature had a more prominent impact on the spring phenological metrics, i.e. Greenup, UD, DES-SOS, TRS₂-SOS, and TRS₅-SOS than precipitation and solar radiation.

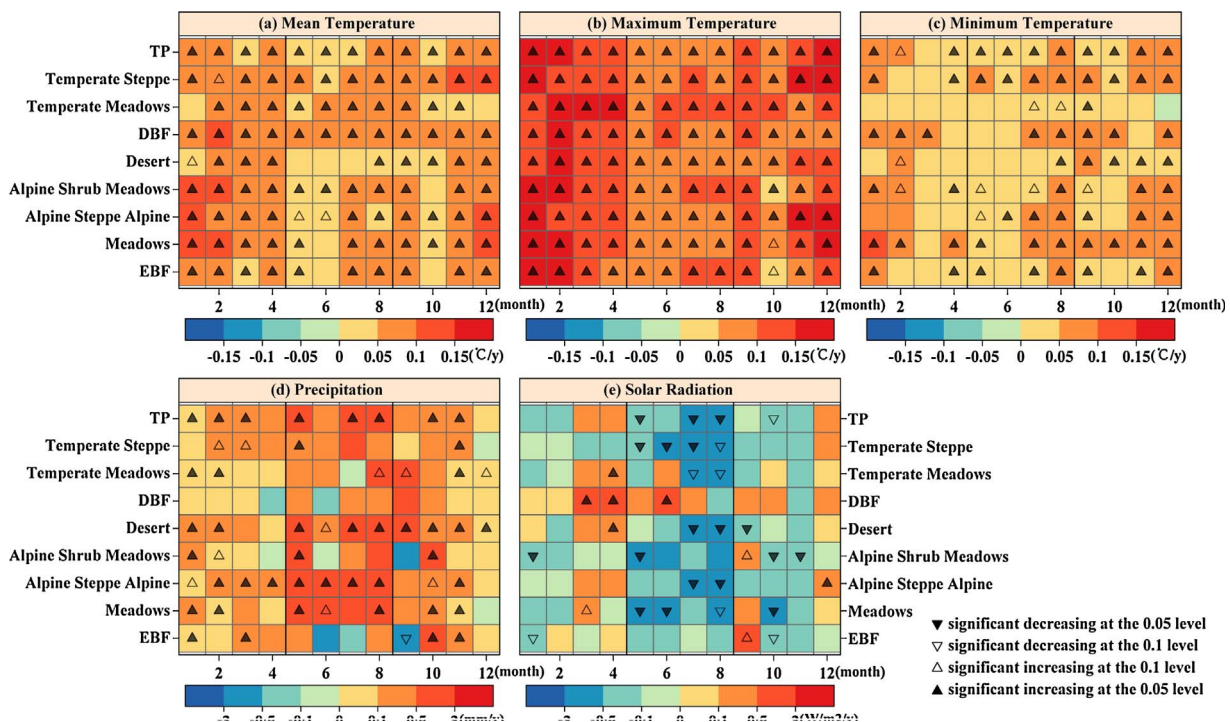


Fig. 6. Trends of average temperature, maximum temperature, minimum temperature, precipitation and solar radiation during 1982–2013.

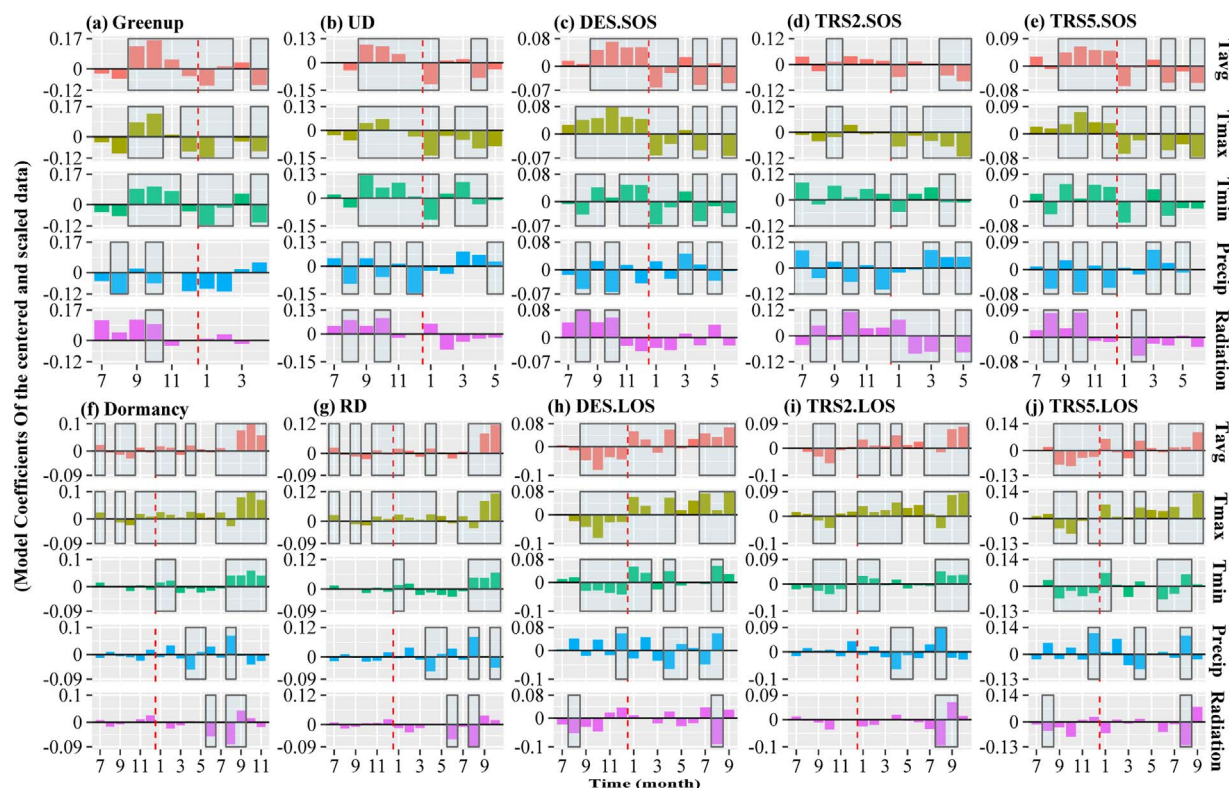


Fig. 7. Coefficients of the partial least regression (PLS) model for the centered and scaled phenological and meteorological data in Alpine meadows. Coefficients depicted by black boxes indicate $VIP \geq 1$; Dashed lines show the end of the previous year; Tavg: mean temperature; Tmax: maximum temperature; Tmin: minimum temperature; Precip: precipitation; Radiation: solar radiation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Generally, the average temperature, maximum temperature and minimum temperature had similar influences on the spring phenological metrics. Furthermore, the average temperature during September to February of the subsequent year had a significant fractional contribution to starting date changes of Greenup, UD, DES.SOS, TRS₅.SOS and increasing temperature during September–December had positive relations with the starting date of growing season and delayed spring phenology (Fig. 7a–c). While the rising temperature during January–February, April and June helped trigger the early date of phenology (Fig. 7a, c and e). Warming climate has the potential to cause early satisfaction of cumulative temperature requirements of vegetation growth and development and will activate enzyme behavior which can help accelerate vegetation phenology. Fig. 6a–e illustrate negative model coefficients, particularly for October and December when significant increasing precipitation occurred during October for alpine meadow but insignificant precipitation changes during December. Precipitation change during March and May had shifts from positive to negative impacts on DES.SOS and TRS₅.SOS (Fig. 7c, e). The positive PLS model coefficients between precipitation of May and UD, TRS₂.SOS, implied earlier starting date defined by UP and TRS₂.SOS (Fig. 3). In addition, positive relations were found between solar radiation during late summer and early autumn of the last year and spring phenological metrics (Fig. 7a–e). However, solar radiation during February–March had negative impacts on TRS₂.SOS and TRS₅.SOS of the very year, which may indicate that higher solar radiation during late summer and early autumn of the previous year potentially causes the delayed autumn phenology (e.g. Liu et al., 2016). Increased solar radiation during February–March implied decreased snow and hence cumulative effective temperature. Besides, increased solar radiation implied lengthening sunshine hours, shortened photoperiod and hence advanced spring phenology.

Temperature change played a key role in driving autumn phenology changes. When compared to maximum and average temperature, the

minimum temperature had weakening impacts on autumn phenological metrics (Fig. 7f and g). Impacts of temperature on autumn phenology were identified during late summer and autumn. During July of the previous year to August of the very year, temperature had undiscernible impacts on autumn phenology. However, the autumn temperature had prominent impacts on the phenology during the end of season of the very year. The temperature of the late summer and solar radiation had negative relations with autumn phenology. Increasing autumn temperature was the key to the postponed autumn phenology.

Temperature was also the key driver of LOS metrics (Fig. 7h–j). The maximum temperature during all months except August had larger impacts on LOS than the minimum temperature. Temperature during September of the last year to April of the very year had remarkable impacts on the spring phenology. However, summer and autumn temperature had critical impacts on autumn phenology, having the potential to shift lengths of the growing season. However, changes of the minimum/maximum temperature during late summer and autumn had distinctly different impacts on LOS. The minimum temperature during August had positive impacts on the phenology and negative impacts of solar radiation were observed on the phenology. This happened because enhancing solar radiation during late summer and autumn increased evapotranspiration and therefore limited vegetation use of water resources. This could be the reason why precipitation change was the key to phenology changes during late summer and autumn. Moreover, precipitation during December and August of the previous year had positive impacts on LOS, but was adverse for precipitation changes during April. This phenomenon can be interpreted by the mechanism that increased precipitation during December of the previous year and August of the very year can increase water availability of vegetation growth. Increased precipitation during April may imply an increase of snow amount in alpine region which greatly limits the occurrence of green-up.

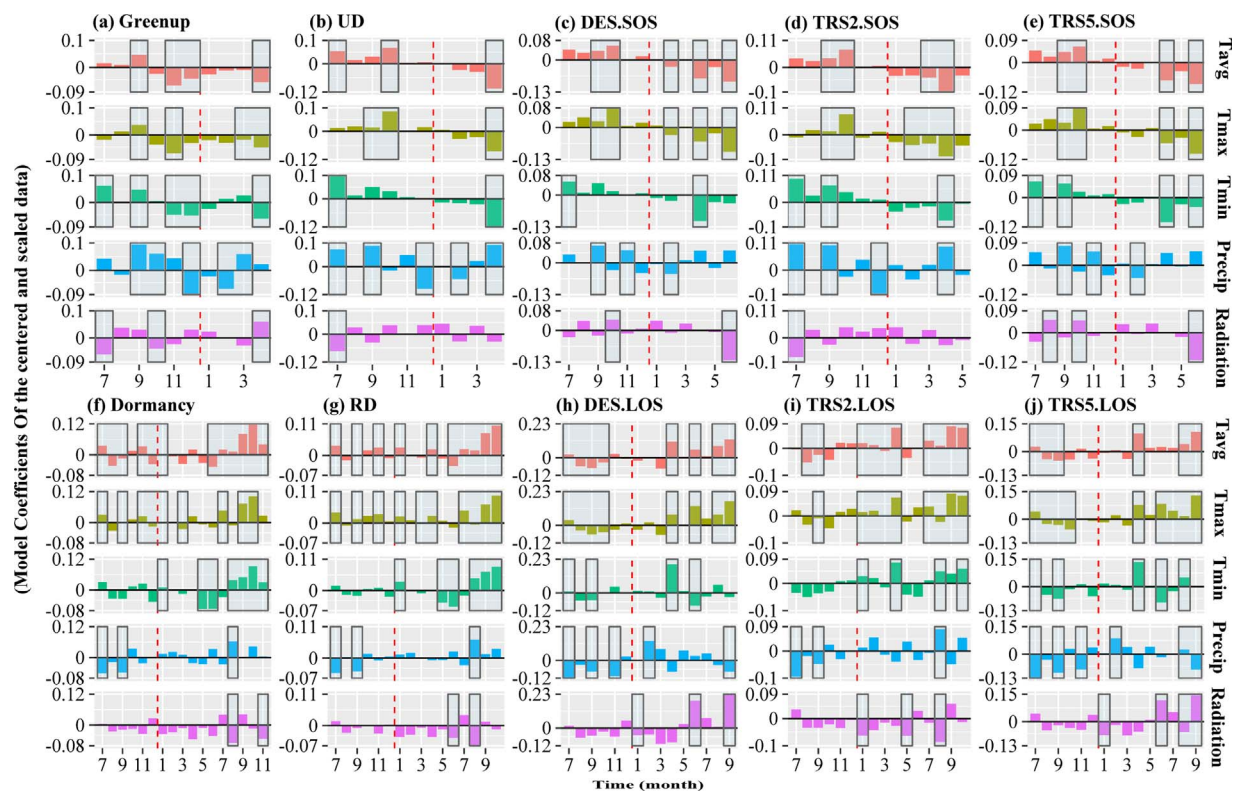


Fig. 8. Coefficients of the partial least regression (PLS) model for the centered and scaled phenological and meteorological data in Alpine shrub meadows. Coefficients circled by black boxes indicate $VIP \geq 1$; Dashed lines show the end of the previous year; Tavg: mean temperature; Tmax: maximum temperature; Tmin: minimum temperature; Precip: precipitation; Radiation: solar radiation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

4.3.2. Climatic impacts on alpine shrub meadow

It can be seen from Fig. 8h–j that a larger variability of the PLS model coefficients can be observed for DES-LOS, TRS₂-LOS, and TRS₅-LOS. Specifically, the PLS model coefficients for solar radiation and precipitation were even in adverse relation with those for the DES-LOS and TRS₅-LOS, which should be attributed to the larger error of the computed TRS₂-EOS and hence the larger variability of growing season length. Temperature had more impacts on spring phenological metrics for alpine meadow than alpine shrub meadow. Similar PLS model coefficients were observed for DES-SOS, TRS₂-SOS and TRS₅-SOS. The temperature of the previous year, particularly temperature during September and October, had positive impacts on spring phenology. However, the average temperature and maximum temperature had negative impacts on spring phenology (Fig. 8c–e). However, the winter average temperature, maximum temperature and minimum temperature had minor impacts on spring phenology in alpine shrub meadow. The average, maximum and minimum temperatures of the last three months had similar impacts on autumn phenology and increasing temperature benefitted the delay of autumn phenology. Increased temperature enhanced photosynthesis and hence postponed autumn phenology (Liu et al., 2016). During May–June, the maximum temperature did not have significant impacts on autumn phenology. However, the impacts of precipitation and solar radiation on autumn phenology were observed mainly during August, which can be interpreted by the key constraints as minimum temperature and precipitation for vegetation growth. Increased solar radiation and maximum temperature reduced the availability of water resources usable for vegetation growth (Shen et al., 2016).

Temperature changes of the previous year had the negative impacts on the length of growing season. Increased temperature did not benefit the dormancy of vegetation (e.g. Yu et al., 2010), and hence had negative impacts on the length of growing season. However, impacts of the temperature of the previous year on the alpine shrub meadow were

detected mainly during late summer and early autumn and the impacts were relatively weak (Fig. 8h, j). However, the average and maximum temperatures during April–September of the very year had larger and positive impacts on the lengthening of growing season. The maximum temperature and solar radiation during June had positive influences on the length of growing season and minimum temperature changes had negative impacts on the length of growing season. The impacts of precipitation on the length of growing season were observed mainly during autumn and winter of the previous year and also during autumn of the very year. However, precipitation of the end of winter of the previous year had positive impacts on the length of growing season, because increased winter precipitation increased the water availability for green-up periods and hence earlier spring phenology. The key factor constraining vegetation growth during autumn of the previous year and the very year were maximum temperature and solar radiation, and increased precipitation had the potential to reduce solar radiation and maximum temperature (Fig. 8h, j).

5. Discussions

Phenological changes are the consequences of complex interactions between temperature, precipitation, solar radiation and many other driving factors as well. Temperature plays the dominant role in the temporal shifting of phenology across the QTP.

In alpine meadow and alpine shrub meadow of QTP, previous year autumn and early winter temperature had a positive effect on the SOS phenology. This phenomenon maybe was the results by two reasons: On one hand, rising temperature in autumn could postpone the previous year EOS, indirectly delaying SOS in the current year; On the other hand, warming in autumn and early winter may slow the fulfilment of chilling requirements in the early stage of vegetation green-up (Yu et al., 2010). Except summer, the minimum temperature had a similar effect on vegetation phenology, as average and maximum temperature.

In alpine meadow, August maximum temperature and solar radiation had a positive influence on autumn phenology. Meanwhile, August minimum temperature had a negative impact on autumn phenology. In alpine meadow, highest temperature and heaviest precipitation both occurred in July. In addition, precipitation in August was sharply decreased. However, August temperature was still quite high, and solar radiation was still strong. They both contributed to a strong evapotranspiration, which could sharply decrease vegetation water availability (Che et al., 2014; Zhang et al., 2017). On the other hand, low precipitation accompanying strong evapotranspiration could increase the prevalence of drought during summer that may subsequently result in earlier leaf senescence (Buermann et al., 2013). The positive correlation of August precipitation and autumn phenology in alpine meadow (Fig. 7f and g) also support this point that in August water availability was the dominant factor constraining vegetation growth and development. Besides, autumn temperature had a positive effect on autumn phenology. Compared with summer, vegetation water requirement was reduced in autumn. And rising temperature will increase the activity of photosynthetic enzyme, slow down the chlorophyll degradation (Liu et al., 2016), and hence result in a postponed autumn phenology.

Precipitation's impact on phenology fluctuated greatly in different month. In alpine meadow and alpine shrub meadow, the PLS model coefficients of precipitation and spring phenology were negative in the last year winter. The increase of precipitation during pre-growing season will increase water availability, and hence advance spring growing season (Shen et al., 2011). In the early spring, the PLS model coefficients turned into negative. This was mainly contributed by that in the early spring, the main form of precipitation was snowfall, which will lead to a low temperature, accompanied with low incoming solar radiation, and handicap vegetation green-up. In alpine meadow, PLS model coefficients of precipitation in May and spring phenology was negative. Temperature was become warm in May, and the main form of precipitation was rainfall, which benefit vegetation coming into spring phenology. In August, the main factor constricting vegetation growth and development was precipitation. And this finding was consistent with Che et al. (2014).

Compared with temperature and precipitation, solar radiation had a limited impact on spring phenology, and its influence mainly concentrated in June, August and September. This is consistent with the conclusion of Liu et al. (2016). Solar radiation mainly determined by a function of latitude and time of year, is not very sensitive to the climate change except under very cloudy conditions (Liu et al., 2016). Probably because solar radiation is mainly due to latitude and is not sensitive to climate change (except for cloudy conditions). In alpine meadows and alpine shrubs meadows, solar radiation in June and August was negatively correlated with autumn phenology. Increasing solar radiation in June can speed up vegetation activities and development, and indirectly lead to an earlier autumn phenology. In August, however water availability became the primary factor constraining vegetation development. The decline of August solar radiation contributed to vegetation activities and accumulation of nonstructural carbohydrate (Fu et al., 2014). Hence decline solar radiation can postpone autumn phenology. In alpine meadow, increasing solar radiation in September will postpone autumn phenology. At that time, high solar radiation can enhance the photosynthetic capacity of vegetation and delay the accumulation of abscisic acid, hence postpone autumn phenology and lengthen growing season.

6. Conclusions

This study attempted to determine the spatiotemporal patterns of phenology and related responses to climate changes across the QTP. 18 phenological metrics were defined to avoid misleading results or viewpoints by some individual phenological metrics. Considering spatial heterogeneity of phenology and different phenology responses to climate changes, 8 vegetation clusters were classified. Besides, PSL

models were developed and used to remove multicollinearity due to correlations between predicted variables and this analysis framework was employed to screen key influencing factors from potential driving factors, such as maximum/minimum temperature, average temperature, precipitation, and solar radiation. The following conclusions can be drawn from this study.

- (1) The spring phenology was subject to abrupt changes during 1997–2000. Spring phenology advanced 2–3d/10a before turning points. Turning points of autumn phenology were identified during 2004–2007. And the length of growing season was subject to abrupt changes during ~2005 with delayed trend about 1–2d/10a. After turning points, changes of the length of growing season were statistically insignificant.
- (2) The PLS regression was one of the appropriate techniques for analyzing phenology changes. Based on PLS regression's results, different climatic variables have different roles in shifting starting/ending time of the growing season during different vegetation phenophases. Temperature plays the dominant role in the temporal shifting of phenology across the QTP. Except summer, the minimum temperature had a similar effect on vegetation phenology, as average and maximum temperature. Precipitation's impact on phenology fluctuated greatly in different months. Autumn and winter precipitation of the previous year had negative impacts on spring phenology. Precipitation during the early spring can had a positive influence on spring phenology. And, precipitation during August was the primary factor constraining vegetation development. Compared with temperature and precipitation, solar radiation had relative minor impacts on phenology changes. And its impact mainly concentrated in June, August, and September.

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